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Uncertainty analysis and global sensitivity analysis of techno-economic assessments for biodiesel production

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HIGHLIGHTS

- Economical feasibility of biodiesel production with uncertainties was assessed.
- Uncertainty analysis and parameter screening was carried out.
- Global sensitivity analysis was performed using three efficient methods.
- Results identified influential parameters on the life cycle cost.

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ABSTRACT

There are various uncertain parameters in the techno-economic assessments (TEAs) of biodiesel production, including capital cost, interest rate, feedstock price, maintenance rate, biodiesel conversion efficiency, glycerol price and operating cost. However, fewer studies focus on the influence of these parameters on TEAs. This paper investigated the effects of these parameters on the life cycle cost (LCC) and the unit cost (UC) in the TEAs of biodiesel production. The results show that LCC and UC exhibit variations when involving uncertain parameters. Based on the uncertainty analysis, three global sensitivity analysis (GSA) methods are utilized to quantify the contribution of an individual uncertain parameter to LCC and UC. The GSA results reveal that the feedstock price and the interest rate produce considerable effects on the TEAs. These results can provide a useful guide for entrepreneurs when they plan plants.

1. Introduction

Conventional fossil fuels can produce many deleterious emissions when igniting in engines, including greenhouse gases, NO_x, hydrocarbons and particulate matter, which have caused various harmful influences on the global climate and air quality (Höök and Tang, 2013; Yan et al., 2014). It is desired to find alternative clean, economic and easy-to-use energy sources in the industry, the transport system, etc. As a renewable fuel, biodiesel has many advantages over the conventional fossil fuels in terms of environmental friendliness (Kalam et al., 2011; Frey and Kim, 2009; Fontaras et al., 2009; Chen et al., 2010). Thus, biodiesel has attracted more and more attention, and the biodiesel industry is growing rapidly. Many studies have focused on biodiesel production from various feedstocks, such as palm oil (Chen et al., 2010), *Jatropha curcas* L. (Yusuf et al., 2012), waste cooking oil (Zhang et al., 2003), soybean oil (You et al., 2008), castor oil (Santana et al., 2010) and vegetable oils (Apostolakou et al., 2009).

In order to understand the economical feasibility of biodiesel production, many researchers have conducted valuable studies on the techno-economic assessments (TEAs) of biodiesel production (Delrue et al., 2012; Nagarajan et al., 2013; Haas et al., 2006; Lozada et al., 2010; Jegannathan et al., 2011; Sakai et al., 2009; Ong et al., 2012). They focused on the life cycle cost (LCC) and the unit cost (UC) of biodiesel production within a project's lifetime under the assumptions that all of the parameters were deterministic. In practice, many unavoidable, uncertain sources exist in the TEAs of biodiesel production during the project's lifetime (Sotoft et al., 2010), such as the variation of the feedstock and biodiesel prices (Busse et al., 2012) and the fluctuation of the interest rate (Mankiw, 2011). As revealed by Borgonovo and Peccati (2006) and Brownbridge et al. (2014), the uncertainties in

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the parameters may exert important effects on the investment projects. In order to decrease these effects, engineers may be interested in knowing the contribution that each parameter has produced on the output and, further, how this contribution can be quantified.

Global sensitivity analysis (GSA) is a beneficial tool to estimate the contribution of an individual parameter to the output. In this paper, three available GSA methods are employed to quantify the contribution of an individual parameter to LCC and UC, i.e., the variance-based importance measure (Saltelli et al., 2004), the moment-independent importance measure (Borgonovo et al., 2011) and the entropy-based importance measure (Tang et al., 2013). The GSA results can serve as a reasonable guide to the identification of the important parameters and the unimportant ones, which can tell the engineers which parameters require attention. The variance-based importance measure (Saltelli et al., 2004) is the most popular GSA tool to test the sensitivity of the output with respect to the random inputs, and it employs the expected reduction in the output variance due to the elimination of the uncertainty in the individual random input to define the effect of the random input on the output. However, as summarized by Borgonovo et al. (2011), the variance-based importance measure may no longer be a computationally advantageous method in the presence of the correlated model inputs. Therefore, the moment-independent importance measure was originally proposed by Borgonovo et al. (2011) as an alternative to the variance-based one. This GSA approach employs the expected shift in the probability density function (PDF) of the output after eliminating the uncertainty in the individual random input to measure the effect. Based on the fact that entropy can measure the uncertainty in a random variable, the authors also proposed an entropy-based GSA method (Tang et al., 2013), which used the expected shift in the entropy to assess the contribution of an individual random input to the output. The three GSA methods can measure the contribution of an individual random input to the output from different physical meanings, i.e., the output variance, the output PDF and the output entropy. Therefore, a combination of them can give a more comprehensive measurement of the contribution of the individual random input to the output.

The paper is organized as follows. Section 2 introduces the TEAs of a biodiesel production and three available GSA methods. Section 3 performs the uncertainty analysis and the global sensitivity analysis for the techno-economic assessments of a biodiesel production under uncertain parameters. Conclusions are given in Section 4.

2. Methods

2.1. Techno-economic assessments of biodiesel production from crude palm oil

Ong et al. (2012) investigated the TEAs of a plant producing biodiesel from crude palm oil with deterministic parameters. Based on this study, LCC and UC are introduced in the following. Then, the variation range of an individual parameter is also provided.

The LCC of biodiesel production from crude palm oil within the project's lifetime is defined by:

$$\mathrm{LCC} = \mathrm{CC} + \mathrm{FC} + \mathrm{OC} + \mathrm{MC} - \mathrm{SV} - \mathrm{BPC}, \tag{1}$$

where LCC is the life cycle cost; CC indicates the capital cost; FC is the feedstock cost; OC denotes the operating cost; MC represents the maintenance cost; SV is the salvage value and BPC is the byproduct credit.

Business and economics commonly employ the present value calculations to compare the cash flows at different times. Therefore, in the form of the present value, LCC is expressed by:

$$\mathrm{LCC} = \mathrm{CC} + \sum_{i=1}^{n} \frac{\mathrm{FC}_i + \mathrm{OC}_i + MC_i}{(1+r)^i} - \frac{\mathrm{SV}}{(1+r)^n} - \sum_{i=1}^{n} \frac{\mathrm{BPC}_i}{(1+r)^i}, \tag{2}$$

where n is the project's lifetime, i.e., $n = 20$; r represents the interest rate, i.e., $r \in [4.44\%, 13.53\%]$ (TRADING ECONOMICS, 2014); FC_i, OC_i, MC_i and BPC_i are the feedstock cost, the operating cost, the maintenance cost and the byproduct credit of the ith year, respectively.

The definitions of all of the items in Eq. (1) will be given. According to Ong et al., 2012, the annual biodiesel production capacity of the plant is 50 ktons, i.e., PC = 50ktons. As revealed by Ong et al. (2012), the capital cost of the plant with such production capacity varies from \$9 million to \$15 million, i.e., CC ∈ [\$9 million, \$15 million].

The main cost of biodiesel production is FC (i.e., the cost of the crude palm oil), which usually accounts for 80–90% of LCC (Hitchcock, 2014) and is expressed by:

$$\mathrm{FC} = \sum_{i=1}^{n} \mathrm{FC}_i = \sum_{i=1}^{n} \frac{\mathrm{FP} \times \mathrm{FU}}{(1+r)^i} = \sum_{i=1}^{n} \frac{\mathrm{FP} \times \frac{\mathrm{PC} \times 1000}{\mathrm{CE}}}{(1+r)^i}, \tag{3}$$

where FP is the feedstock price or the crude palm oil price, which varied from \$200/ton to \$1200/ton in the past twelve years, FP ∈[\$200/ton, \$1200/ton] (Ong et al., 2012); FU is the annual total feedstock consumption; CE represents the conversion efficiency from feedstock to biodiesel, which generally varies from 96% to 99%, i.e., CE ∈ [96%, 99%] (Nagi et al., 2008).

The total OC within the project's lifetime in the form of the present value model yields, which usually comprises less than 15% of LCC (Duncan, 2003), is defined by:

$$\mathrm{OC} = \sum_{i=1}^{n} \mathrm{OC}_i = \sum_{i=1}^{n} \frac{\mathrm{OR} \times \mathrm{PC} \times 1000}{(1+r)^i}, \tag{4}$$

where OR is the operating rate or the operating cost of per-ton biodiesel production. Here, the percentage that FC comprises in LCC takes the value of 80% (Hitchcock, 2014), and the percentage that OC comprises in LCC is 15% (Duncan, 2003). Because the feedstock price is FP ∈ [\$200/ton, \$1200/ton] (Ong et al., 2012), the operating rate or the operating cost of per-ton biodiesel production can be approximated as OR ∈ [\$37.5/ton, \$225/ton] by the feedstock price.

The total MC within the project's lifetime is formulated by:

$$\mathrm{MC} = \sum_{i=1}^{n} \mathrm{MC}_i = \sum_{i=1}^{n} \frac{\mathrm{MR} \times \mathrm{CC}}{(1+r)^i}, \tag{5}$$

where MR denotes the maintenance rate. MR takes a value of 2% in the research of Ong et al., 2012, and it is 1% in the work of Haas et al., 2006. Here, MR varies from 1% to 2%, i.e., MR ∈ [1%, 2%].

Salvage value (SV) is the remaining value of the components and the assets of the plant at the end of the project's lifetime, which is defined by:

$$\mathrm{SV} = \mathrm{RC} \times (1-d)^{n-1} \times \mathrm{PWF}_n = \frac{\mathrm{RC} \times (1-d)^{n-1}}{(1+r)^n}, \tag{6}$$

where d is the depreciation rate, i.e., $d = 5\%$; $n = 20$ is the project's lifetime of the plant; RC is the replacement cost, i.e., RC = \$10 million (Ong et al., 2012); PWF_n is the present worth factor in the year n.

For the plant producing biodiesel from the crude palm oil, the byproduct credit comes from the sale of glycerol, which is yielded during biodiesel production. The total amount of the byproduct credit during the project's lifetime is defined by: